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Intelligent Control Technique for Autonomous Collective Robotics Systems

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Abstract—**The paper considers the problem of finding maximum number of the radiation sources that are located on the plain field by group of mobile agents with limited time. We formulate both physical and mathematical models that describe the environment and the behavior of mobile agents by including a topology of communication between agents. We propose MPSO-Optima which is improved version of Particle Swarm Optimization (PSO) algorithm adapted to changes in the velocity directions by the conjugate gradient method and optimizing magnitude of the inertia ratio. Both improvements lead to the higher convergence rate that proved by numerical experiments. As a result of the study, the method demonstrates increased resistance to the variation of the acceleration coefficients. The algorithm is tested on virtual simulator environment.**

Keywords—particle swarm optimization (PSO); mobile agents; search for radiation sources; inertia center; method of conjugate gradients.

INTRODUCTION

The development of intellectual system for autonomous robotic control will allow solving actual problems in the space research and the enterprise automation, to reduce risks while working in dangerous conditions to rescue people in a case of natural and technological disasters to promote intelligence in the defense technology.

The main complexity of the modern application development for mobile robots is to introduce an effective management in the conditions of uncertainty and fuzzy information, to take into account the requirements in a rapid response for constantly changes in the environmental conditions. The autonomous robotic control systems must also provide the movement planning under non-deterministic conditions on the basis of the knowledge base by taking into account the continuously incoming information to the control system from sensors and navigation system. All those requirements determine a complexity of the autonomous control system for group of robots.

The main characteristics of collective multi-robots control are: presence of own decision-making criteria for all agents; delays in the transmission of data streams and control actions between members of the system; uncertainty in parameters of the distributed system, which is represented by different approaches depending on how data is retrieved (measurement or expert assessment). It raises a question of the selection and the evaluation of the objective function for finding the global optimal solution of the system as a whole. Moreover, the complexity of the selection and the evaluation repeatedly increases in the case of the collective work for multi robots [18]-[26].

Noawadays, many techniques are being developed for the multi-agent interaction within a group of robots and for monitoring of open and closed spaces and territories. These tasks can be solved by the methods of forming strategies for behavior of groups of robots that are processed primarily on the use of network technology cooperation between robots within a group. The intellectual control technology for robotic team is reflected in a number of publications that are based on multi-agent approaches[3], optimization algorithms, an imitation of the ant colony optimization [4], [5], [6], Particle Swarm Optimization (PSO) [7] and the principles of Q-learning [8], [9]. In existing approaches, the usage of different design criteria for autonomous distributed dynamic systems requires different objective functions that often do not show a clear influence on all characteristics of the designed system. To avoid this problem, in [10] it is proposed the use of two modes of evaluation criteria for the distribution of tasks (goals) between robots in two modes: on-line and off-line. However, the authors [10] for the task allocation in a heterogeneous group of mobile robots formulated the organizational problem of robots coalition for each task. But it is not taken into account, for example, the criteria of reliability and cost minimization. In other words, the optimization of one parameter leads to a substantial change for other criteria.

Furthermore, there are problems of the communication between agents in a view of high intensity as a result of interactions and, therefore, in a lack of the system control as a whole.

In the context of strong interference from the environment there is an important question whether the mobile robot can perform the own task without help from the team [1], [10], [18]-[25]. In practical conditions, a communication between robots in a search for radiation sources may be prevented by heat sources, high concentrations of gaseous radioactive substances (radon), features of the terrain, and weather conditions. Also, a failure of given robot should not significantly affect a feasibility of the global mission [5].

In the paper we propose MPSO-Optima which is modification of the PSO algorithm that can dramatically

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reduce search time of point sources (thermal, radiation, chemical) for robots.

In Section 2 we give physical formulation of the problem, describe the general physical characteristics of radiation sources and agents, introduce a notion of the limit of the minimum time for which agents can detect all sources, propose a precise mathematical definition of the intensity distribution of the field sources and a description of the topology of communication between agents.

In Section 3 we describe MPSO-Optima that is the modification of PSO which allow to adjust a coefficient of the inertia on approaching agents to the radiation sources, and thereby optimize the speed of convergence of the algorithm. In the modified method, a coefficient of the inertia is considered as a vector. This assumption allows to achieve a faster convergence of the algorithm.

Section 4 is devoted to a description of the method of numerical experiments, and the results obtained. The results of the experiments are presented in graphical form. The dependence of the convergence of iterative processes from the number of agents and sources is discussed.

PROBLEM STATEMENT

Nowadays, the radiation hazards of coal mines in Kazakhstan, associated with natural radionuclide contained in coals and rocks, are one of the important and neglected problems of the coal industry. The gamma radiation has great penetrating power and creates an external exposure to miners. The second major problem of coal mine is fires. During endogenous fires at coal mine the different types of gases are generated, for example carbon dioxide and radon. As a result of coal heating, the radon diffuses toward the surface through cracks and gobs.

This problem is solved by the proposed location of the team of robots to search for sources of radiation. To test the proposed method will simplify the physical formulation of the problem. Consider a flat field, which is deployed on a group of robots $P = \{P_i, i \in [1:N]\}$ to search for sources of radiation $T = \{T_r, r \in [1:M]\}$, where M - number of sources, N - number of robots in a team. Location of agents defined by the vector of coordinates $X_i^t = (x_{i1}^t, x_{i2}^t, \dots, x_{in}^t)$ and the velocity vector $V_i^t = (v_{i1}^t, v_{i2}^t, \dots, v_{in}^t)$ in n-dimensional space R^n. All agents are divided into $h = \overline{1,N}$ groups Gr_j for $j = \overline{1,h}$. The number of groups and the number of particles in the groups are variable and depend on the relative positions of the particles.

The number and the location of sources are initially unknown. To simplify the mathematical formulation of the problem assumes that sources are as points. The same problem is not considered in the temporal variation of the radiation intensity. For short periods this simplification is justified.

An intensity of radiation decreases inversely proportional to the square of the distance from radiation source

$$I_r(X) = \frac{I_{max}}{(X - X_{r0})^2}, \tag{1}$$

where X_{r0}, I_{max} are a coordinate and an intensity of the radiation source.

At each point X of field the intensity $I(X)$ is a sum of the intensities $I_r(X)$ of all M sources:

$$I(X) = \sum_r I_r(X). \tag{2}$$

An example of field intensities for a single source at different distances from the center line is shown in Fig. 1.

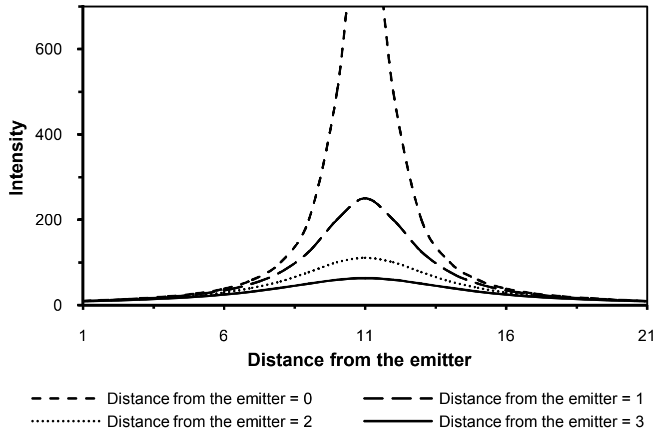

Fig. 1. Example of field intensities for a single point source of radiation at different distances from the centerline

The agents are able to measure the intensity of radiation at fixed location, store and pass it to agents who are within receiving range.

Also the agents can move across the field at the rate not exceeding the maximum velocity V_{max}. The challenge is to find the agents of all radiation sources in the minimum time.

The radiation source is considered found an agent if the agent is closer predetermined distance d from the source. Agent who found the source of radiation remains near him until the end of simulation cycle.

Each agent i is located at the distance D_{ij} from source j. There is always a minimum D_i^{min} for all the possible distances. The sum of all agents $D^{min} = \sum D_i^{min}$ shows how accurately the algorithm closer to the discovery of all sources. Therefore, D^{min} is a good indicator for assessing the effectiveness of the algorithm.

Estimated minimum time it takes the agent i to reach the nearest source of power:

$$t_i^{min} = \frac{\left(D_i^{min} - d\right)}{V_{max}}. \tag{3}$$

If we sum this time for all agents, having the time of which will find all sources is physically impossible.

$$T^{min} = \max_i t_i^{min}. \quad (4)$$

This time is a theoretical limit to evaluate the effectiveness of the algorithm. The closer the time in which an algorithm allows you to find all sources of radiation to the limit T^{min}, so that the algorithm is considered efficient. In a real time environment T^{min} is unattainable.

In the task it is assumed that the agent is able to instantly turn on the spot at any angle. Thus, the reversal does not contribute to the total time of the algorithm.

One of the effective ways to solve this problem is a particle swarm optimization method (PSO) [14]. In this case, the robots are particles. According to the classical PSO algorithm at each instant time, and in particular for each iteration, the particles are considered in the search space of optimal solutions for position and velocity vector. At each position of the particle it was calculated the corresponding value of the objective function on the basis of which the particle changes its position and speed in the search space according to the relevant prescribed rules.

At the initial time *t = 0*, the position and the velocity P_i of a particle are equal to $X_i^0 = (x_{i1}^0, x_{i2}^0, \dots, x_{in}^0)$ and $V_i^0 = (v_{i1}^0, v_{i2}^0, \dots, v_{in}^0)$. In subsequent times *t = 1,2,3,…* the position P_i of the particle is calculated by the iterative vector equation:

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \quad (5)$$

$$V_i^{t+1} = W \cdot V_i^t + G \cdot rnd_G \cdot (G^{best} - X_i^t) + L \cdot rnd_L \cdot \left(L_i^{best} - X_i^t\right), \quad (6)$$

where $L_i^{best} = max\{X_i^0, X_i^1, \dots, X_i^t\}$ - a vector of the best position for *i-th* particle in the preceding time $t = \overline{0, t_{max}}$ The best position is defined as a coordinate at which the *i-th* particle is at the point with the maximum intensity from the source group *T;*

$G^{best} = max\left\{L_k^{best}, L_l^{best}, \dots, L_m^{best}\right\}$ - a vector of the best position of the particle within the group Gr_j. The indexes $k, l, \dots, m = \overline{1, N}$ are a number of particles within the group Gr_j;

$W > 0$ - a coefficient of the inertia. It defines the balance between breadth of research and thorough study of local solutions. If $W > 1$, then a velocity of the particles increases. They rapidly spread across and carefully examine space. In the case $1 > W > 0$ a velocity of the particle decreases over time;

rnd_G and rnd_L - vectors of random numbers uniformly distributed in the interval *[0,1];*

$G > 0$ - a social factor that determines the acceleration with which the group looking for the best position;

$L > 0$ - a cognitive factor that determines the acceleration with which the individual looking for the best position.

There are some types of the method. In this study, a modification of the method of multi-swarm particles migration MPSO (PSO with migration) is applied [8], [12]. At the beginning of each step agents are divided into groups. Each agent has its own identification number. Starting from the smallest identification number each agent communicates with the agents, separated from it by a distance less than pre-specified distance, global positions. Physically, this means that each agent has a limit on the range of communication. All agents who find themselves within the field of communications belong to a group of the first agent. Thus, at the beginning of each step agents are separated into groups. The number of members in a group can vary from one to the total amount of agents in the field. Within a group, all the agents are considered to be neighbors with each other, that form fully meshed graph or clique [9]. As agents converge, the number of groups generally decreases, and at the end of the process is equal to the number of detected sources.

In this paper, we propose to adjust the direction of the velocity of the particles by the method of conjugate gradients [2], and specify the value of the coefficient of inertia by calculating the standard deviation of the particle coordinates of the center of inertia of the group [13]. Correction of the velocity distribution of the particles in the directions, and the inertia ratio, allows us to find the optimal solution for each robot in the team and for the community as a whole.

PROVIDES AN IMPROVED METHOD FOR FINDING THE OPTIMAL SOLUTION

For representation we developed a modified method of MPSO-Voptima considers the deployment of three agents shown in Fig. 2, which is calculated by (5) – (6).

Let at time step $t - 1$, the agents X_1, X_2 and X_3 had a velocity vector V_1^{t-1}, V_2^{t-1} and V_3^{t-1}, respectively. Agents seek to maintain a constant velocity. Modules of velocities depend on the scalar factor W in (6). Since the coefficient is not a vector, a direction of the velocity is always constant, but it may change their modules.

Also, for each agent, there are still two more vectors. One of these vectors indicates the best local position, which active agent is held in one of the preceding steps.

The result of adding the direction vectors of the best local position and global best position of the three agents is shown in Fig. 2. The resulting velocities for the step t are obtained by vector addition of velocities V_1^{t-1}, V_2^{t-1} and V_3^{t-1} with those velocities V_1, V_2 and V_3, shown in Fig. 2. The calculated velocities become current and allow agents to move to new positions in accordance with (5).

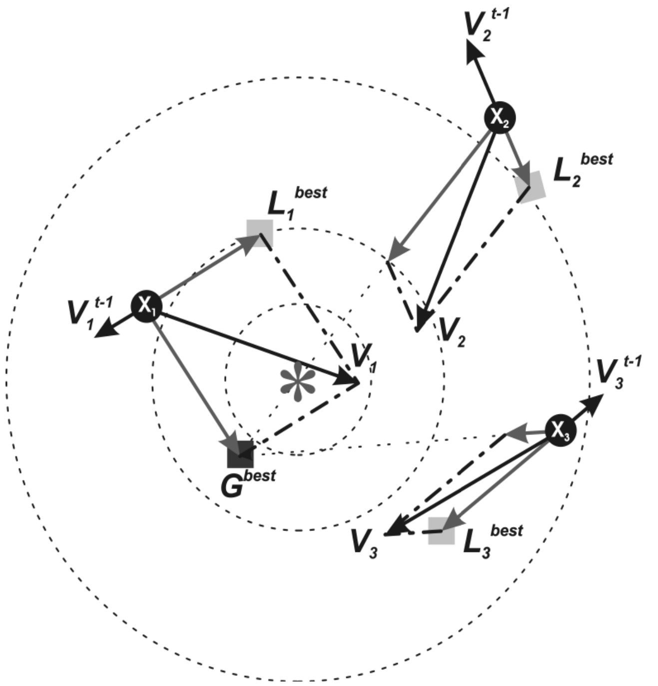

Fig. 2. Vectors direction toward the best local and global positions for three agents: * - position of a point source of radiation --- - equipotential lines of the source, ● - agent positions, ■ – local and global positions.

In the Fig. 3 these positions are marked by gray rectangles L_1^{best}, L_2^{best} and L_3^{best}. The cognitive L and stochastic rnd_L components are influenced to a module of these vectors. The cognitive component L is a scalar and does not change a direction of the vector, and the modulus of the stochastic parameter rnd_L is a random variable in the interval *[0,1]*. The stochastic component rnd_L rotates a direction of the vector $L(L^{best} - X)$ between 0^0 and 90^0. An example of the parameter action is shown in Fig. 3.

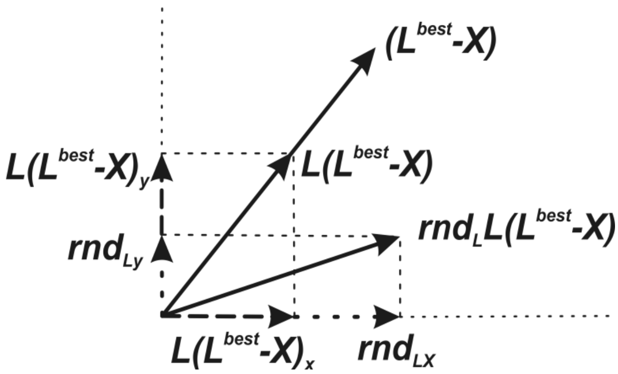

Fig. 3. Possible vector directions

The second vector indicates the direction of the best global position for a group of agents. The position was held by one of the agents of the group at the previous time moment. The best global position is marked with black box G^{best} in Fig. 2. The module of the vector is also affected by two factors. One of the factors G changes the vector module $(G^{best} - X)$, and second rnd_G changes direction.

In the proposed method MPSO-Voptima the usage of conjugate gradients method allows to direct the agent speed along the optimal path, and the refinement of the intensities by the standard deviation method optimizes the module of the inertia factor in a separate group.

The equation (6) can be rewritten as follows:

$$V_i^{t+1} = W \cdot \left(V_i^t + \frac{G \cdot rnd_G \cdot (G^{best} - X_i^t)}{W} + \frac{L \cdot rnd_L \cdot \left(L_i^{best} - X_i^t\right)}{W} \right). \tag{7}$$

Now all three terms in the brackets can be considered as increment of the coordinates $\Delta^t X_i$. The expression for the velocity can be rewritten in the form of functional dependence $V_i^{t+1} = W \cdot f(\Delta^t X_i)$

At the initial time $t = 0$ for each agent $i = \overline{1, N}$, where N - number of agents randomly on the coordinates of the two-dimensional coordinate plane X_i^0, Y_i^0 and the initial velocity vector V_i^0. The components of the vector coefficient W_i^0 are set equal to each other and equal to the initial value. At the location of the *i-th* agent the scalar field intensity I_i^0 is measured or calculated.

On subsequent iterations $t = 1,2,3,$ ... the new position of each agent is evaluated by (5) and (6). If the calculation gives a velocity exceeding the allowed maximum, or less than the permissible minimum, it is necessary to make normalization by the following rule:

$$\|V_i^t\| = \sqrt{(V_{xi}^t)^2 + \left(V_{yi}^t\right)^2},$$

$$if\ \|V_i^t\| > \|V_{max}\|\ then \begin{cases} V_{xi}^t = V_{xi}^t \cdot \left(\dfrac{\|V_{max}\|}{\|V_i^t\|}\right) \\ V_{yi}^t = V_{yi}^t \cdot \left(\dfrac{\|V_{max}\|}{\|V_i^t\|}\right) \end{cases}, \tag{8}$$

$$if\ \|V_i^t\| < \|V_{min}\|\ then \begin{cases} V_{xi}^t = V_{xi}^t \cdot \left(\dfrac{\|V_{min}\|}{\|V_i^t\|}\right) \\ V_{yi}^t = V_{yi}^t \cdot \left(\dfrac{\|V_{min}\|}{\|V_i^t\|}\right) \end{cases}.$$

At the new position the field intensity I_i^t is measured again.

The gradient is calculated for the current step

$$D_i^t = \nabla I(X_i^t) = \frac{\Delta I_i}{\Delta X_i}, \tag{9}$$

where $\Delta I_i, \Delta X_i$ - an increment of the field intensity and the agent coordinate, respectively Since we approach to the radiation source the intensity increases monotonically, and therefore the gradient has a positive value.

If the intensity of the field at the current position was less than the intensity of the previous iteration, the velocity vector is directed in the direction of the calculated gradient. Otherwise, the rate will be unchanged.

$$\|D_i^t\| = \sqrt{(D_{xi}^t)^2 + (D_{yi}^t)^2},$$

$$if\ I_i^t < I_i^{t-1}\ then \begin{cases} V_{xi}^t = D_{xi}^t \cdot \left(\frac{\|V_{max}\|}{\|D_i^t\|}\right) + \beta^{FR} V_{xi}^t \\ V_{yi}^t = D_{yi}^t \cdot \left(\frac{\|V_{max}\|}{\|D_i^t\|}\right) + \beta^{FR} V_{yi}^t \end{cases}, \quad (10)$$

where β^{FR} - coefficient, calculated from the Fletcher-Reeves equation for quadratic functions [2]:

$$\beta^{FR} = \frac{\|D_i^t\|}{\|D_i^{t-1}\|}, \quad (11)$$

where $\|D_i^t\|$ - denotes the norm of the gradient vector calculated in the present iteration, $\|D_i^{t-1}\|$ - the norm of the gradient vector computed in the previous iteration.

These calculations are made for each agent separately.

Further calculations should be carried out on groups of agents Gr_j. For each group the position of the inertia center is calculated separately [13]

$$\overline{X_h^t} = \frac{\sum_{i=1}^{N_h} X_i}{N_h}, h = \overline{1, N}, \quad (12)$$

where $\overline{X_h^t}$ - the vector coordinates of the inertia center of the *h-th* group, N_h - the number of particles in the group *h*. Thereafter, for each agent within the group, it is computed a standard deviation [13]

$$\sigma_h^t = \frac{\sqrt{\sum_{i=1}^{N_h}\left(\left(x_{xi}^t - \overline{x_{xh}^t}\right)^2 + \left(x_{yi}^t - \overline{x_{yh}^t}\right)^2\right)}}{2N_h - 1}, \ h = \overline{1, N}. \quad (13)$$

From the change in the standard deviation for the current and previous iterations it can be concluded the correction of inertia coefficient [13]:

$$\begin{aligned} &if\ \frac{\sigma_h^{t-1}}{\sigma_h^t} < 0.7\ then \begin{cases} W_{xi}^t = 1.2 \cdot W_{xi}^t \\ W_{yi}^t = 1.2 \cdot W_{yi}^t \end{cases}, \\ &if\ \frac{\sigma_h^t}{\sigma_h^{t-1}} > 0.7\ then \begin{cases} W_{xi}^t = 0.8 \cdot W_{xi}^t \\ W_{yi}^t = 0.8 \cdot W_{yi}^t \end{cases}. \end{aligned} \quad (14)$$

The rules in (14) are generally in the correction module inertia ratio depending on the amount of change of the standard deviation of the position coordinates agents center of inertia group. If the difference is increased by an amount greater than the experimentally found value of 0.7, the components of the inertia ratio reduced by 20%, and if reduced by the same amount, then the components of inertia ratio must be increased by 20%. An increase and a decrease of 20% inertia weight is the experimentally for the problem.

After all the adjustments there is a transition to a new iteration *t = t + 1*.

The proposed method makes it possible to optimize the value of the inertia weight as we approach the sources. In the initial stages of the coefficient is set large enough to allow the agents can be studied as a larger portion of the plane. In the final stages of the algorithm coefficient decreases, this allows agents to pay more attention to is the earliest possible approximation to the source than to find new sources.

NUMERICAL EXPERIMENTS

To carry out the numerical experiment, we have developed the software simulator, which allows to carry out several series of calculations at the same locations of the radiation sources and for the same initial distributions of agents (see Fig. 4). The experiments were carried out for different amounts of agents in the field, and for different amounts of radiation sources. The location of radiation sources was arbitrary, but it was consistently for one series of experiments.

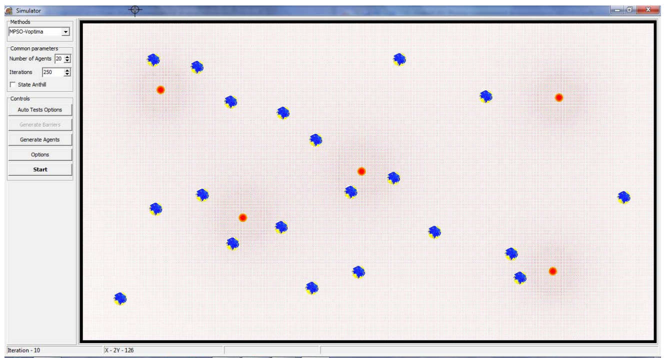

Fig. 4. Simulator for the numerical experiments

For methods of PSO and MPSO-Voptima inside each test it was performed an additional series of tests with different values of the coefficients *W, G* and *L* (see Table 1). The change of the coefficients *G, L* was linear with steps ΔG, ΔL. For given internal runs the initial random configurations were repeated. The parameters of the experiment are presented in Table 2.

TABLE I. VALUES OF COEFFICIENTS IN THE TESTS

Tests	Coefficients		
	W	*G*	*L*
Тест 1	0.5	1.5	0.5
Тест 2	0.5	1.5	1
Тест 3	0.5	1.5	1.5
Тест 4	0.5	2	0.5
Тест 5	0.5	2	1
Тест 6	0.5	2	1.5
Тест 7	0.5	2.5	0.5
Тест 8	0.5	2.5	1
Тест 9	0.5	2.5	1.5
Тест 10	1	1.5	0.5
Тест 11	1	1.5	1
Тест 12	1	1.5	1.5
Тест 13	1	2	0.5
Тест 14	1	2	1
Тест 15	1	2	1.5
Тест 16	1	2.5	0.5
Тест 17	1	2.5	1
Тест 18	1	2.5	1.5
Тест 19	1.5	1.5	0.5
Тест 20	1.5	1.5	1
Тест 21	1.5	1.5	1.5
Тест 22	1.5	2	0.5
Тест 23	1.5	2	1
Тест 24	1.5	2	1.5
Тест 25	1.5	2.5	0.5
Тест 26	1.5	2.5	1
Тест 27	1.5	2.5	1.5

TABLE II. GENERAL PARAMETERS OF EXPERIMENTS

The Parameter	The Value
The initial value of the coefficient *W*	0.5
The number of consecutive gain values *W*	3
Step changes in the coefficient *W*: ΔW	0.5
The initial value of the coefficient *G*	1.5
The number of consecutive gain values *G*	3
Step changes in the coefficient *G*: ΔG	0.5
The initial value of the coefficient *L*	0.5
The number of consecutive gain values *L*	3
Step changes in the coefficient *L*: ΔL	0.5
Full velocity $\|\|V_{max}\|\|$	4
The minimum velocity $\|\|V_{min}\|\|$	1
The number of iterations in each test	250

As soon as the certain agent approached the source at a distance equal to its radius, the source is considered as detected by agent. If there are multiple sources, the distance is the distance to the nearest source. If the agent, for any reason, begins to move to the remote source, it affected the efficiency of the proposed algorithm.

The processing was performed as follows. Firstly, the total distances toward the nearest sources were averaged for the entire series of experiments and for each iteration. Secondly, to smooth the differences in the initial configuration the averaging was performed over ten runs.

The Table 3 shows an extract of the resulting distances from the MS Excel spreadsheet for the case of 20 agents and five sources. The Analytical solutions column determines the theoretical line calculated by (4).

TABLE III. RESULTS FOR 20 AGENTS AND FIVE SOURCES

Iteration	Algorithm		Analytical Solution
	PSO	*MPSO-Voptima*	
0	3050.326	3050.326	3050.326
10	2707.61	2770.741	2250.326
20	2349.127	2467.446	1450.326
30	1965.656	2130.203	650.3258
40	1601.633	1791.665	0.0
50	1271.191	1477.081	0.0
60	1045.064	1199.773	0.0
70	897.0246	957.3589	0.0
80	788.4594	802.653	0.0
90	724.5369	681.3491	0.0
100	682.442	573.8899	0.0
110	650.8333	464.8374	0.0
120	608.7718	397.7523	0.0
130	583.0021	340.2163	0.0
140	573.7791	307.6085	0.0
150	568.7102	272.5916	0.0
160	573.5614	250.4561	0.0
170	553.9541	223.2127	0.0
180	533.5306	221.6779	0.0
190	520.7146	218.6462	0.0
200	511.3651	217.6933	0.0
210	505.4151	205.9661	0.0
220	499.1633	206.7525	0.0
230	485.4537	200.4798	0.0
240	485.9743	205.9789	0.0
250	482.4218	204.4708	0.0

As a result were obtained graphs of the rate of approximation to the sources for different values of the number of robots and sources shown in Fig. 5-6.

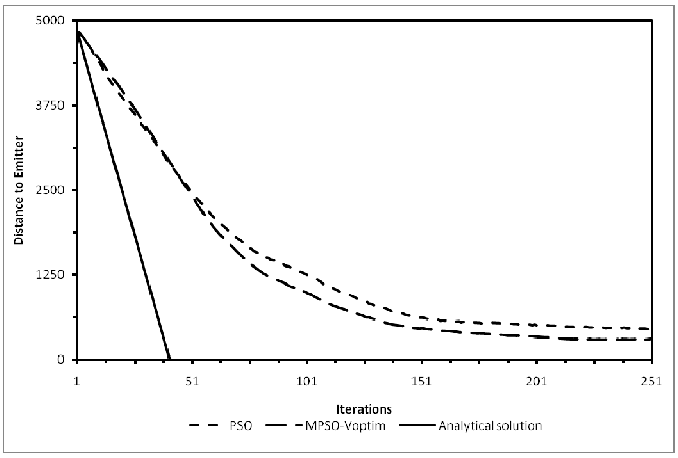

Fig. 5. The speed of convergence of the algorithms to 30 agents and 5 sources

Figures added to the theoretical straight line, showing the physical limit, which, in theory, agents, having complete information about the coordinates of each source can be at the maximum permitted velocity to get to the nearest source. Any algorithm that does not have completes information, and hence, any algorithm will run slower and give a theoretical calculation curve located to the right of the theoretical.

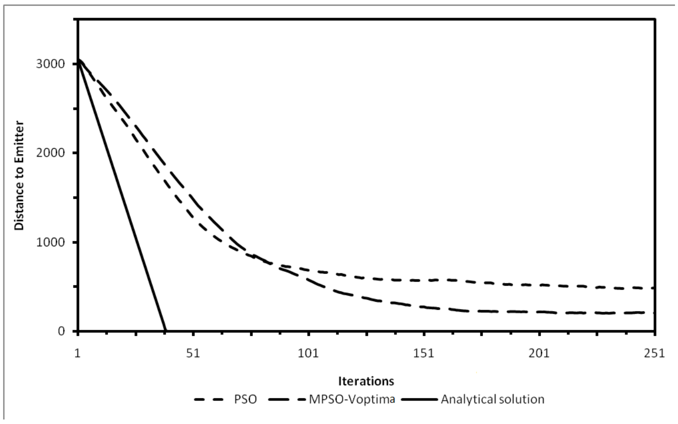

Fig. 6. The speed of convergence of the algorithms to 20 agents and 5 sources

The Fig. 7 shows a plot of a small number of agents. Since the difference between the graphs in this case is less than the graph shows data only with the 100-th iteration of greatest interest.

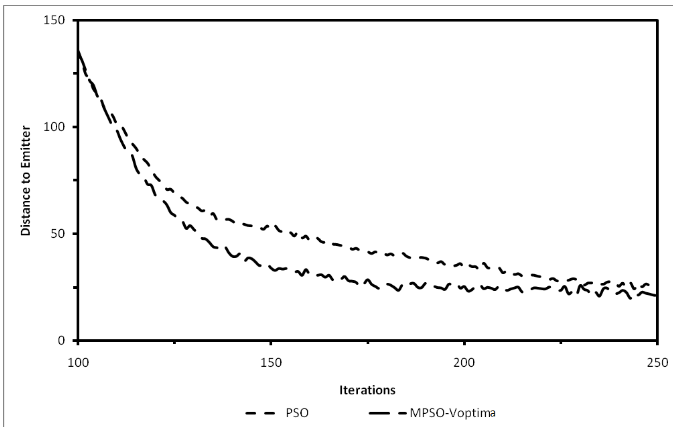

Fig. 7. The speed of convergence of the algorithms to 6 agents and 3 sources

From the analysis of the graphs can draw several conclusions. Modified algorithm shows good results if the number of agents is equal to 20-30. This can attribute to that the coefficients in (14) are found experimentally for this number of agents. With a decrease in the experiment robots collective component of the algorithm becomes less efficient. Inertia weight changes quickly enough and preference is given to the individual search abilities of individual agents. But at the same time for each agent still has a strong influence in the social component of (6). The direction of the velocity gradient gives a small contribution to the resulting vector.

Reduced efficacy of a modified algorithm for large quantities of agents can be explained by lack of flexibility of the coefficients (14).

For a small number of agents is greatly influenced by the initial favorable location. Graphics methods for PSO and MPSO-Voptima in the early iterations are practically the same. But after accumulating agents sufficient information on the direction of the gradients of the modified particle swarm method shows better results, since the direction of the velocity is practically indicates maxima of the function and there is a rapid convergence of the method.

In order to test the presented approach we have constructed prototypes of mobile robot shown in Fig.8.

Fig. 8. Mobile robot for testing the approach

In future work we are planning to develop web-application that demonstrates proposed decentralized approach in the real world and builds two-dimensional map of the environment and found radiation resources in the on-line mode.

CONCLUSIONS

Despite the fact that the particle swarm optimization method proposed has been actively studied at this time, there is the possibility of further modifications and optimization, particularly when applied to real problems group control agents.

The proposed method of the inertia ratio optimization allows to accelerate a convergence of the algorithm with a slight increase in the volume of calculations.

The method is a combination of two algorithms. The first component is based on the long-known conjugate gradient algorithm. This method is one of the fastest gradient optimization methods can achieve the minimum of n steps, where n - the dimension of the search space. Particularly good results have demonstrated the method when applied to a quadratic function. Application of the method of conjugate gradients to the problem of finding sources of radiation is justified back to the quadratic dependence of the intensity of the radiation field on the distance from the source. Calculations are made for each agent alone, and it allows you to optimize the inertial component of (6).

The second component of the method aims to improve the collective behavior of agents. Agents are divided into groups and each group is computed center of inertia. According to the provisions of the remoteness of each agent on the position of the center of mass can judge the effectiveness of the group and adjust her work.

Numerical calculations show that our method has a faster convergence when applied to the problem of finding a large group of mobile agents' radiation sources than the classical method of PSO. The developed algorithm can reduce the search time without significantly increasing the volume of calculations. Search time is of great practical importance in the use of mobile robots in a fleeting technological disaster.

The convergence rates of the classical PSO method and the modified method are indistinguishable for a very large number of agents. In the future we plan to explore the impact of the coefficients in (14) on the rate of convergence of the algorithm for different quantities involved in the agent search.

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